Domain Adaptation using Passive and Active Approaches

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GitHub: Lab work and presentation

Follows the steps:

- Go to link https://github.com/sagihaider/CEEC_2018
- Look at right hand side in green color: Clone or download. Click it and Download Zip
- When downloading is finished. Copy the Zip file and take to the location you want such any folder and paste it. Extract it.
- If you have **Anaconda3** installed. Go to terminal or command prompt and type "jupyter notebook"

Outline

Shifts in Data

- Dataset Shift
- Types of Dataset Shift
- Causes of Dataset Shift

Learning in Dataset Shift: **Domain Adaptation**

Notation

- A set of features or covariates X.
- A set of target or class variables Y.
- A joint distribution P(Y,X) or $P(Y \cap X)$ (i.e. Probability of Y and X).
- $(X \rightarrow Y)$: Y is determined by values of X (e.g. credit card fraud detection) Predictive models (e.g. Logistic Regression, SVM, and Neural Networks.)
- $(Y \rightarrow X)$: Y determines the values of X (e.g. medical diagnosis) Generative models (e.g. GMM, HMM, and Naive Bayes).
- The joint distribution P(Y,X) can be written as
  1. $P(Y|X)P(X)$ in $X \rightarrow Y$ problems.
  2. $P(X|Y)P(Y)$ in $Y \rightarrow X$ problems.
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Issues with Data in Machine Learning

- Imbalanced dataset
- Overlapping dataset
- Density: Lack of data
- Noise in data
- Dataset Shift

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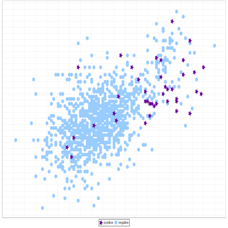

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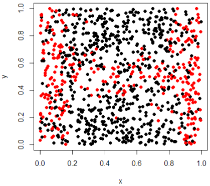

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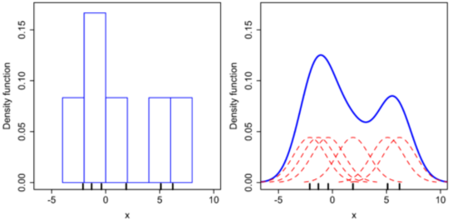

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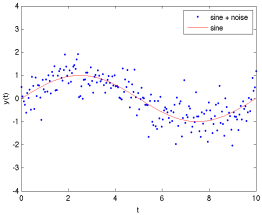

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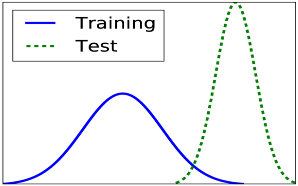

Motivation

- In learning theory independent and identically distributed (i.i.d) assumption (i.e. each random variable has the same probability distribution as the others and all are mutually independent).
- In practice train and test inputs have different distributions.
- The difference in distribution arises from operating in non-stationary environments in real-world application such as finance, healthcare, brain signals, much more...
- Learning in such non-stationary environment is difficult and we need an think before operating.

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Shifts in Data

Outline

Dataset Shift

- "cases where the joint distribution of inputs and outputs differs between training and test stage"[1]

1. "concept shift/drift" G. Widmer et al., 1996, 1998
2. "changes of classification" K. Wang et al., 2003
3. "changing environments" R. Alaiz-Rodrıguez et al., 2008
4. "fracture point" N.V. Chawla et al., 2009
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Dataset Shift: General Example

- Speech recognition system
- Training the speech recognition system
- Voice recognition systems fails

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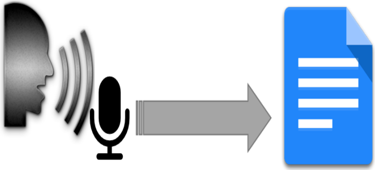

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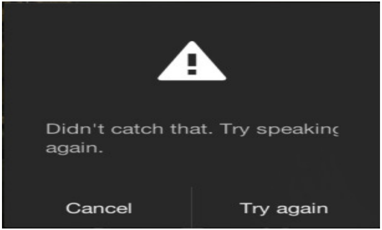
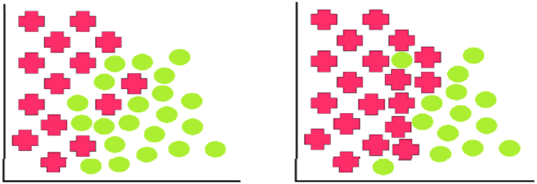


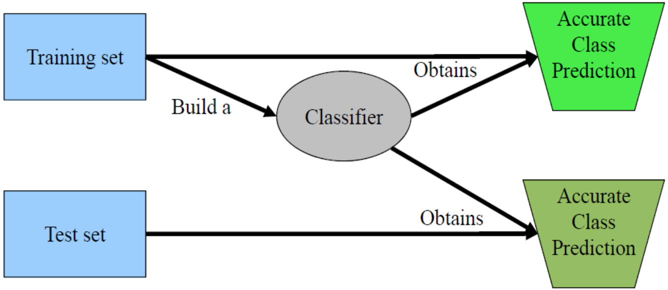
Dataset Shift...cont

- **Dataset shift** appears when training and test joint distributions are different. That is, when $P_{tr}(X,Y) \neq P_{ts}(X,Y)$



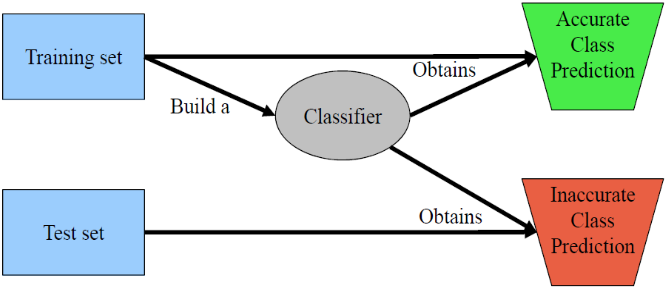
Dataset Shift...cont

- Basic assumption for classification in operating under stationary environment



Dataset Shift...cont

- But sometimes...



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Dataset Shift...cont

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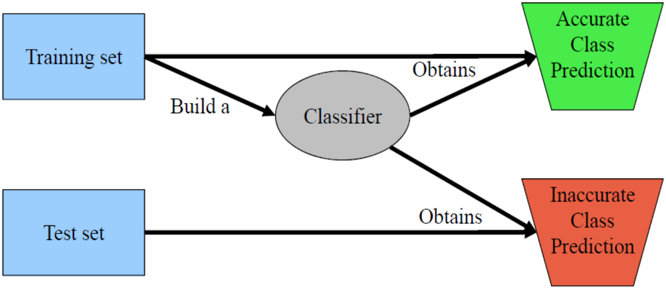

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The problem of Dataset Shift

- **If** the classifier has an overfitting problem: **then** possible actions
  - Change the parameters of the algorithm
  - Use a more general learning method
- **If** there is a change in the data distribution between training and test sets: **then** possible actions [2]
  - Train a new classifier for the test set
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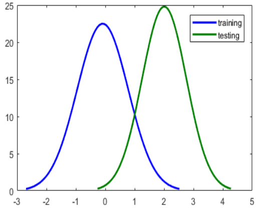
$$P_{tr}(X) \neq P_{ts}(X)$$

Uni-variate



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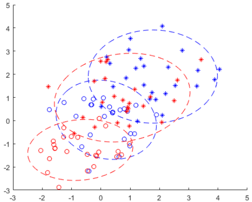

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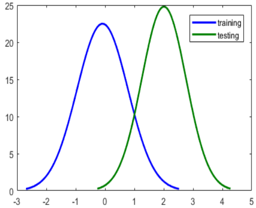

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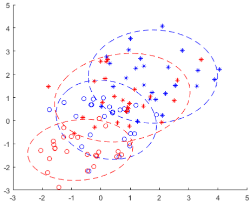

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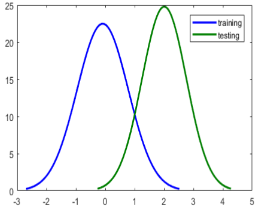

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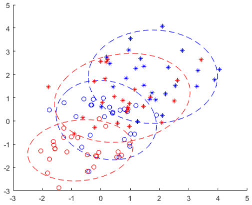

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Covariate Shift: An Example

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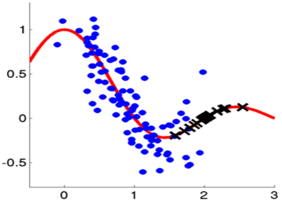

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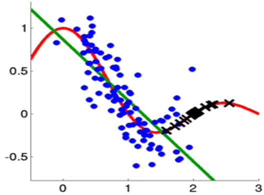

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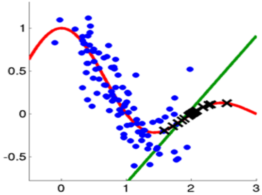

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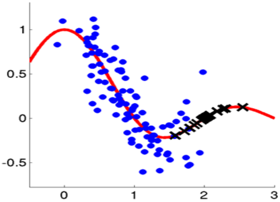

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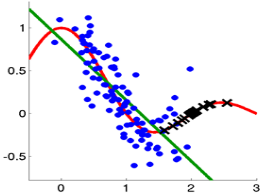

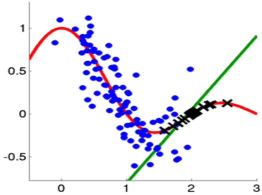

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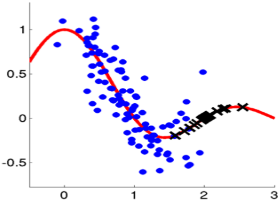

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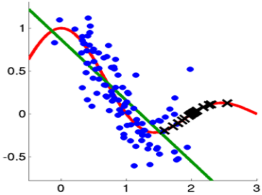

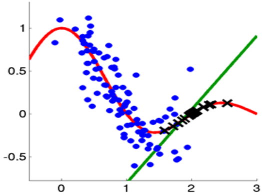

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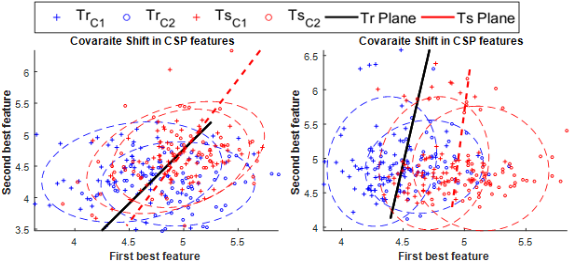
Covariate Shift: An Example

- A Classification example [5]



- Covariate shift (CS) between the training and test distributions of the EEG signal from the healthy subject (a) illustrates the CS in the mu band [8-12] Hz and (b) shows the CS in the beta band [14-30] Hz.

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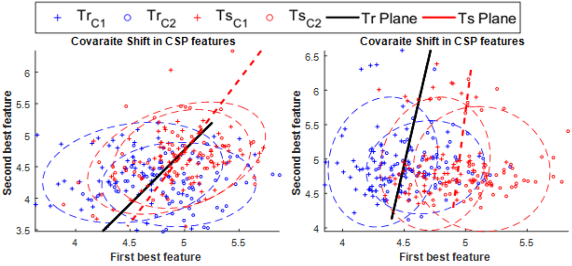

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Prior probability shift

- Prior probability shift appears only in Y $\rightarrow$ X problems, and is defined as the case where

$$P_{tr}(Y \mid X) = P_{ts}(Y \mid X)$$

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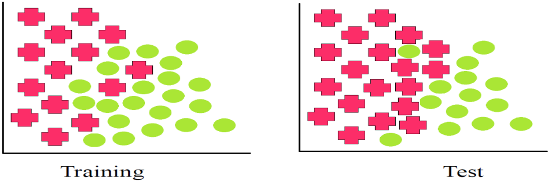

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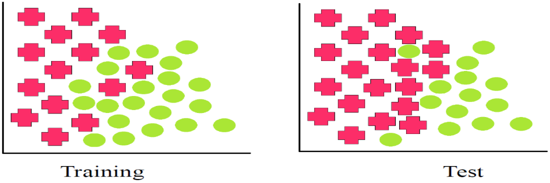

Prior probability shift: Example

Example [6]: $Y \rightarrow X$ problem with one covariate x_0 and a target y that may take the class value $y{=}0$ and $y{=}1$. In training data, $P_{tr}(y=0) = P_{tr}(y=1) = 0.5$ and $P_{tr}(x_0 \mid y)$ is defined as

$$x_0 = \begin{cases} \mathcal{N}(2, 0.5), & \text{when } y = 1 \\ \mathcal{N}(-2, 05), & \text{otherwise} \end{cases} \quad (1)$$

Now consider that in the test data $P_{ts}(x_0 \mid y = 0)$ and $P_{ts}(x_0 \mid y = 1)$ remains unchanged, but the class prior probabilities vary, taking the values $P_{ts}(y = 0) = 0.70$ and $P_{ts}(y = 1) = 0.30$. This example is illustrated in the figure below

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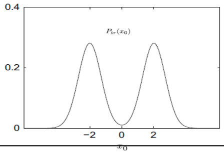

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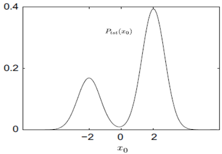

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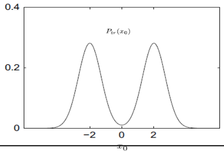

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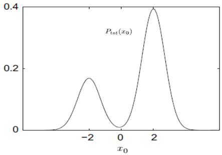

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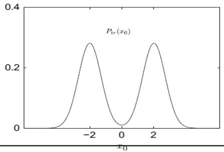

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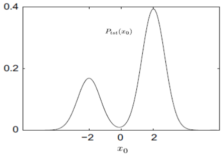

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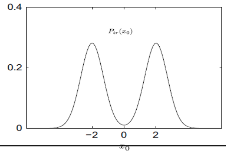

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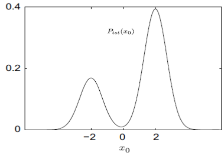

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Concept Shift

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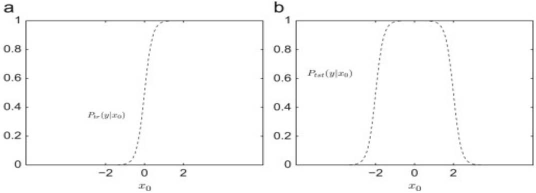

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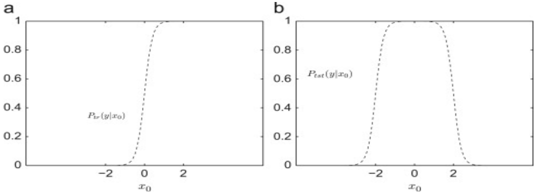

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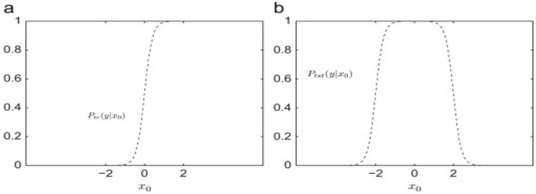

Outline

Shifts in Data

- Dataset Shift
- Types of Dataset Shift
- Causes of Dataset Shift

Learning in Dataset Shift: **Domain Adaptation**

Causes of Dataset Shift

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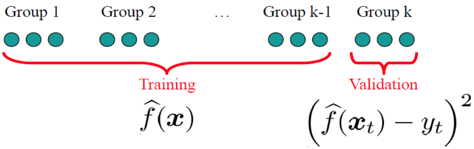
Correcting: Dataset shift generated by Sample Selection Bias

1. Divide the training samples into k groups.
2. Train a learning machine with $k-1$ groups.
3. Validate the trained machine using the rest.
4. Repeat this for all the combination and output the mean validation error.



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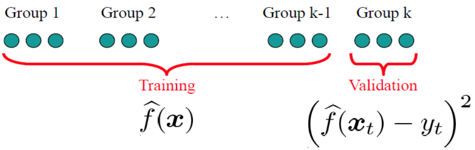

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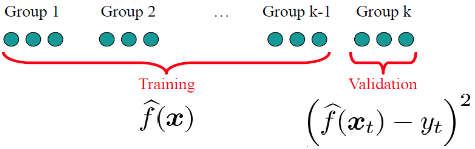

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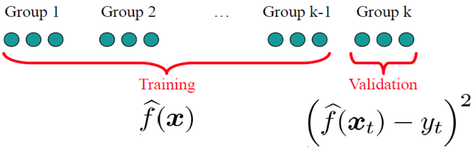

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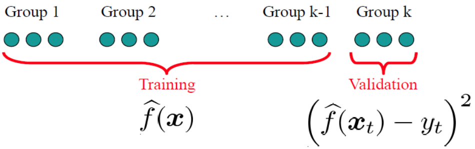

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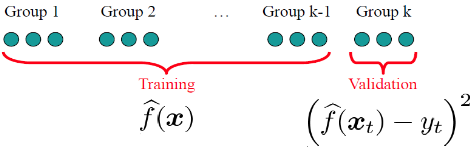

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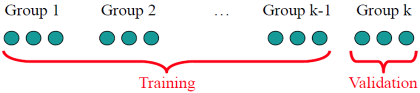

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Learning in Dataset Shift: **Domain Adaptation**

Learning in Non-stationary environments

Ditzler, G et al., (2015). Learning in Nonstationary Environments : A Survey. *IEEE Computational Intelligence Magazine*, 10(4), 12–25.

Learning in Non-stationary environments: Domain Adaptation

Domain Adaptation scenario arises when we aim at learning from a source data distribution (Training distribution) a well performing model on a different (but related) target data distribution (Testing distribution).

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   - Provide lower computational cost.
   - Decision trees are the most common classifier for data stream mining.
   - Very Fast Decision Tree (VFDT) and Online Information Network (ONI) are very popular approaches based on sliding window method.
   - Recently, Extreme Learning Machine (ELM) based on neural networks gaining popularity for learning non-stationary data.
2. **Ensemble Classifier**:
   - More accurate than single classifier due to reduction in the variance of the error.
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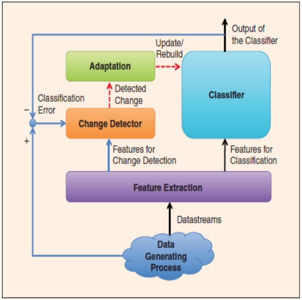
Passive Approaches Methods

1. **Single Classifier**:
   - Provide lower computational cost.
   - Decision trees are the most common classifier for data stream mining.
   - Very Fast Decision Tree (VFDT) and Online Information Network (ONI) are very popular approaches based on sliding window method.
   - Recently, Extreme Learning Machine (ELM) based on neural networks gaining popularity for learning non-stationary data.
2. **Ensemble Classifier**:
   - More accurate than single classifier due to reduction in the variance of the error.
   - Flexible to incorporate new data, simply by adding new members to ensemble.
   - Provide mechanism to forget irrelevant knowledge, simply by removing old classifiers.

Active Approaches Methods



It is based on change detection mechanism that triggers, whenever advisable, an adaptation mechanism aiming at reacting to the detected change by updating or building new classifier.

Active Approaches Methods

1. **Change/Shift Detection**:
   - Hypothesis Test, Change-point methods, Sequential hypothesis test, and Change-detection test.
   - Popular methods: EWMA, CUSUM, JIT, ICI, DDM and many more.
2. **Adaptation**:
   - Supervised adaptation, unsupervised adaptation, semi-supervised adaptation, and transduction.
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Domain Adaptation

- Learning from a source (training) data distribution a well performing model on a different (but related) target (testing) data distribution.
- Example, one of the tasks of the **common spam filtering problem** consists in adapting a model from one user (the source distribution) to a new one who receives significantly different emails (the target distribution).
- Note that, when more than one source distribution is available the problem is referred to as **multi-source domain adaptation.**
- Iterative Domain Adaptation Algorithm
  1. a model h is learned from the labeled examples;
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- Causes of dataset shift.
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